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DETECTION OF HUMAN GENDER FROM EYES IMAGES USING DNN APPROACH

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Abstract

Gender identification is a crucial technique that can enhance the performance of authentication systems. Due to its variety of applications, human gender detection, a component of face recognition, has drawn a lot of interest. Previous studies on gender identification have relied on static features of the body, such as the face, eyebrows, hands, bodies, fingernails, etc. This study focuses on the use of machine learning and deep learning techniques for gender identification in face recognition systems. The abundance of face picture datasets has enabled the development of several effective models. In this study, the effectiveness of pre-trained deep neural network (DNN) models is examined when there is a lack of data. To address this issue, only the areas of the one eye picture with brows were used to classify the gender, instead of the entire face. The results of the study indicate that the EfficientNetb7 model is the best, with an accuracy of 0.913, outperforming other models such as Xception (accuracy of 0.876), InceptionResNetV2 (accuracy of 0.892), VGG16 (accuracy of 0.902) and Resnet50 (accuracy of 0.905). Overall, the study highlights the importance of accurate feature extraction and the effectiveness of DNN models for gender identification in face recognition systems.

Keyword: *Eye region, Facial data, DNN, Gender Classification, Artificial Intelligence*

1. INTRODUCING

The use of artificial intelligence nowadays resolves a number of issues with human recognition. In many applications, including security, monitoring, context-based index, human-computer interaction, epidemiological studies, and biometrics, gender categorization is crucial[1]. Automated gender identification is often approached as a two-class classification issue, in which two-class classifiers are trained using characteristics derived from a collection of photos corresponding to male and female people. It has taken up a lot of room in the facial recognition sector. Due to rapid transmute of the human face, identifying a person's gender from facial data is likewise a difficult problem nowadays. When a person's face changes, such as when they grow a beard or a moustache or as they age, the effectiveness of the procedures may quickly deteriorate[2]. The position of the head might have an impact on it as well.

To address these issues and produce reliable findings, researchers have created a variety of methodologies and models that have been documented in literature. The traditional method used in face recognition, including face-based gender recognition, generally entails the phases of picture capture and processing, dimensionality reduction, feature extraction, and classification, in that sequence. The ideal feature extractor to develop will depend on prior understanding about the application area. Additionally, the type of classifier used, which in turn depends on the feature extraction technique had been using, has a significant impact on how well the recognition system performs. Finding a classifier that works well with the selected feature extractor in order to obtain the best classification performance is challenging. Any modifications to the issue domain necessitate a whole system redesign[3].

The major goal of this study is to identify the gender of a person from their eyes using image processing techniques to extract features based on appearance and Deep Neural Networks (DNNs) to classify the gender of a person. In this regard, we provide a unique DNN-based method for real-time gender categorization. Gender identification from face photos is limited in this study to gender identification from eye images. As a result, the dataset and area of interest are both limited. In this work, many cutting-edge DNN models that have not been used on that particular classification issue are used on a well-structured dataset of eye pictures since pre-trained DNN models exhibit extremely promising results on image classification challenges[4].

Despite the fact that gender categorization might be crucial in many computer vision applications, it has not received as much research as the more well-known issues of recognition and identification. The majority of current pattern recognition systems start with heuristic-based feature extractors followed by trainable or non-trainable classifiers. This section summarizes earlier efforts from the standpoint of the categorization techniques used.

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The study develops a dataset made up of face photographs of Caucasian and Malaysian individuals and using several convolutional neural network techniques using (CNN) architectures to classify people by gender[5]. Using the VGG16, ResNet-50, and MobileNet models, it reports accuracy of 88%, 85%, and 49%, respectively. The study employs over 1500 face photos, the majority of which were taken from the CASIA collection. It creates a CNN and obtains a gender categorization accuracy of 98.5 percent[6]. The research done to create a deep learning approach for identifying the gender of pedestrians. Preprocessing was used to separate the pedestrian from the image. Then, stacked auto encoders and a softmax classifier were used for classification. Humans can easily identify the gender of most faces, and other clues from clothes, body type, brows, hairdo, and posture will complement the evidence from the visual image. Researchers have also explored the acoustical variances between male and female voices, and they can make a significant impact. Beginning in the early 1990s, studies on gender categorization using face photographs were conducted. Using a multi-layer neural network, gender was first assigned to human faces in 1990[7]. They used a back-propagation image compression network in the Cantrell style and reported a gender categorization error rate of 8.1%. Since then, gender classification applications have been explored widely in many other fields, leading to the formation of gender classification methodologies, from which the iris, hand shape, and eyebrows have been regarded as characteristics in the literature. Picture quality problems can arise even during the image capturing process due to issues with noise, poor resolution, and dithering. The feature extraction & classification algorithms have an impact on the classification procedures as well. A research suggests using a straightforward CNN to boost gender categorization accuracy. On the Adience dataset, promising accuracy results have been attained. The Hyperface approach, which is based on Resnet-101 CNN, is suggested. The gender recognition rate and speed are both increased by this strategy[8].

Titive and Bouzerdoum were among the first to suggest gender categorization by integrating feature extraction and classification in a single neural network. On the FERET face database, their method, which used a brand-new shunting inhibitory convolutional neural network (referred to as SICoNNets), had an average classification accuracy of 97.1 percent. A shunting inhibitory neuron with two activation functions and one division task was primarily responsible for the improved performance. In this work, multiple state-of-the-art DNN models that have not been utilized on that particular classification issue are employed on a well-structured dataset of eye pictures[9].

2. RESEARCH METHODS

The rest of the work is structured as follows. Previous studies on gender categorization are covered in Section 1 .The research methodology and dataset utilized in this investigation is briefly described in Section 2, along with the specifics. The findings of the categorization are shown in Section 3. Finally Section 4, concludes the work completed and providing recommendations for future work.

There are various face datasets that have been utilized in the literature for gender categorization, including Adience, FERET (color-feret-database), Gallagher's dataset, and LFW[6], [10]. However, they all offer images of the entire face, and for the researchers, segmenting the eyes is an extra task. We utilize the dataset known as "Female and Male" since this study exclusively compares state-of-the-art DNN models using photos of the eyes. Only the eye pictures that were taken from photographs of the entire face are included in this collection. Keep in mind that it typically also involves either the entire brow or a portion of it. Additionally, it has 6323 male and 5202 female eye photographs as shows in figure 1. Examples of this dataset's images of female and male eyes are shown in Figures 1 and 2.

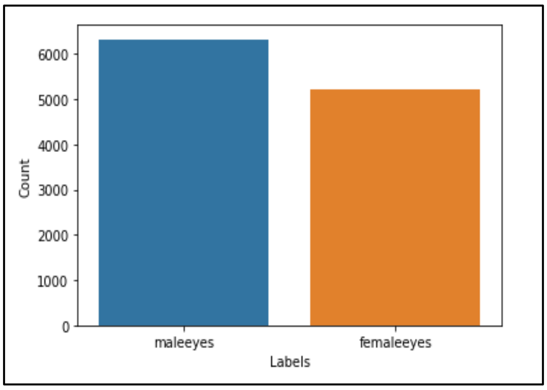

Figure 1: Detail of male and female eye in term of number of the images

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To find out how well various cutting-edge, pre-trained deep learning models can identify gender from eye pictures. The basis models utilized for this are Xception , InceptionResNetV2 , VGG16 ,Resnet50 and EfficientNetb7. To shield the network from a potential overfitting issue, dropout layer is utilized.

Table 1: Training Parameter of the DNN.

Parameter	Value
Optimizer	Adam
shuffle	True
loss	Categorical Cross entropy
No of epochs	100
Batch size	32

Each eye picture in the dataset is standardized in this study to eliminate the impact of various lighting conditions. To train and evaluate the deep models, we employ 4-fold cross validation. For a better result as a regularizer and to lessen overfitting, data augmentation is used using the parameters rotation with 30, zoom at 0.15, shift range is 0.2, shear range is 0.15, and horizontal flip. The image dataset is first separated into four equal halves via randomization as shows in Figure 2. As a result, for each fold, 80% of the eye photos are designated as the training set with parameter shows in table 1 and 20% as the test set. The training is carried out in a Python environment with Keras. The images have been resized to 100x100. In conclusion, the aforementioned DNN-based methods show promise for obtaining higher performance in recognition issues, and gender categorization in particular.

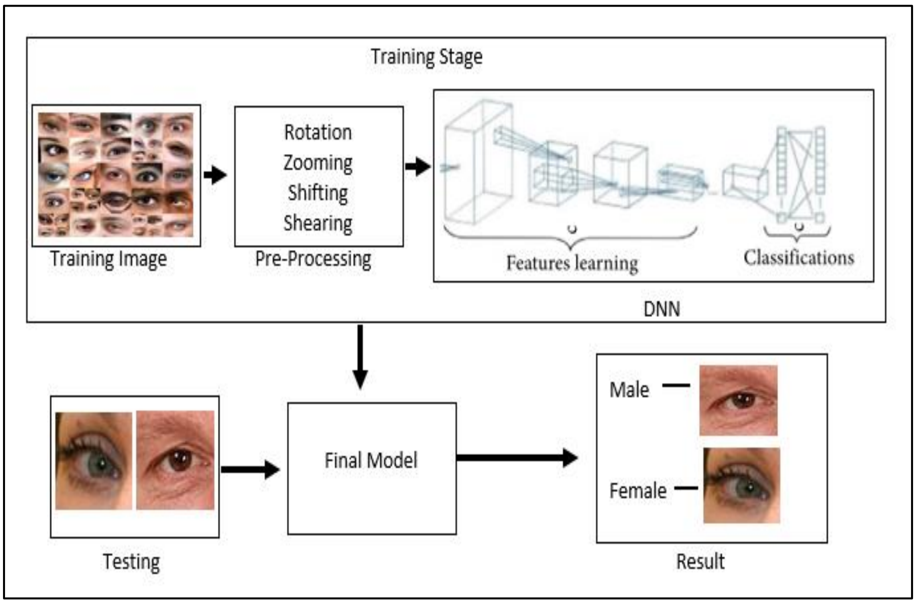

Figure 2: Block Diagram of the proposed methodology

3. RESULT AND DISCUSSIONS

The purpose of this study is to examine how gender may be determined from eye pictures using deep models that have been previously trained. These include Xception, InceptionResNetV2, VGG16, Resnet50, EfficientNetb7, the most effective pre-trained deep models. Tables 2 provide the mean confusion matrices for several deep models. The general

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mean accuracy and standard deviation, which are derived from the folds' accuracy scores, are shown in the right-bottom corner of each table. Additionally, the mean ratings for Recall, Precision, and F1 are shown very promising categorization performances are handled, as seen in the table below.

Table 2: Classification report of all the models by using precision, recall, F1 score and accuracy.

Models	Gender	Precision	Recall	f1-score	Accuracy
VGG16	Female eyes	0.86	0.87	0.87	0.883
	Male eyes	0.9	0.89	0.9	
ResNet50	Female eyes	0.88	0.92	0.9	0.912
	Male eyes	0.9	0.89	0.92	
ResNetV2	Female eyes	0.81	0.93	0.86	0.872
	Male eyes	0.94	0.83	0.88	
Xception	Female eyes	0.85	0.9	0.88	0.887
	Male eyes	0.92	0.88	0.9	
EfficientNetb7	Female eyes	0.92	0.88	0.9	0.913
	Male eyes	0.91	0.94	0.92	

Although all of the models utilized in this study produce excellent results, EfficientNetb7 is chosen as the top model based on accuracy as shows in figure 3, recall, precision, and F1 scores.

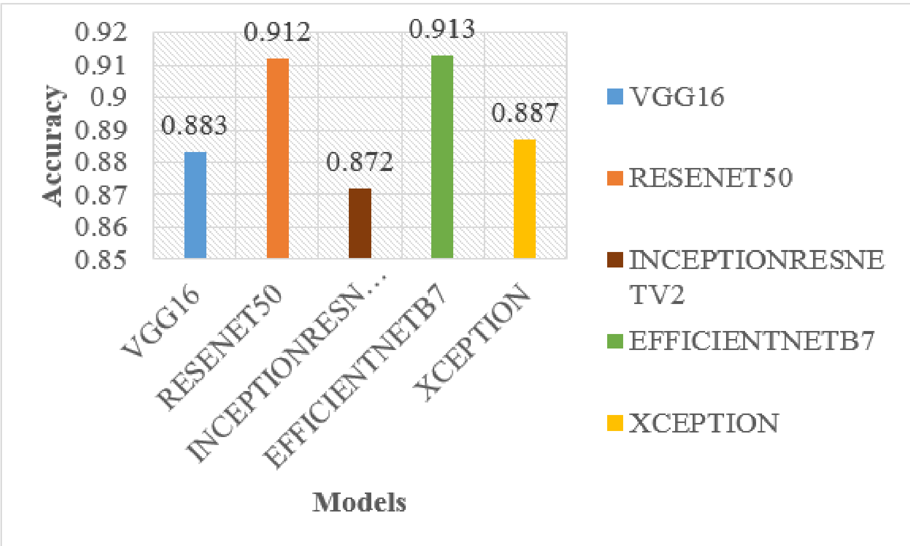

Figure 3. Shows the best model as an EfficientNetb7 on the basis of their accuracy.

Although all of the models utilized in this study produce excellent results, EfficientNetb7 is chosen as the top model based on accuracy as shows in figure 3, recall, precision, and F1 scores.

4. CONCLUSION

The classification performance of four cutting-edge deep neural network models—Xception, InceptionResNetV2 VGG16, Resnet50, and EfficientNetb7—on the categorization of gender from eye pictures is shown in this paper. The

"Female and Male" dataset was used to train these models. The findings demonstrate that even when the face data is restricted to the region around a single eye, the accuracy, recall, precision, and F1 scores are still extremely good. This demonstrates that the characteristic points on the eye area are crucial for determining gender. This is because to the physical variations in eye shape, slant, and brow shape and smoothness between male and female eyes. All of the models used are quite effective, however the EfficientNetb7 model is the best based on accuracy.

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